ACCURACY COMPARISON OF TWO MULTIPLE-SENSOR WIM ALGORITHMS

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- Introduction and objectives
- Static weight estimation algorithms
- Experiment
- Results and analysis
- Conclusions

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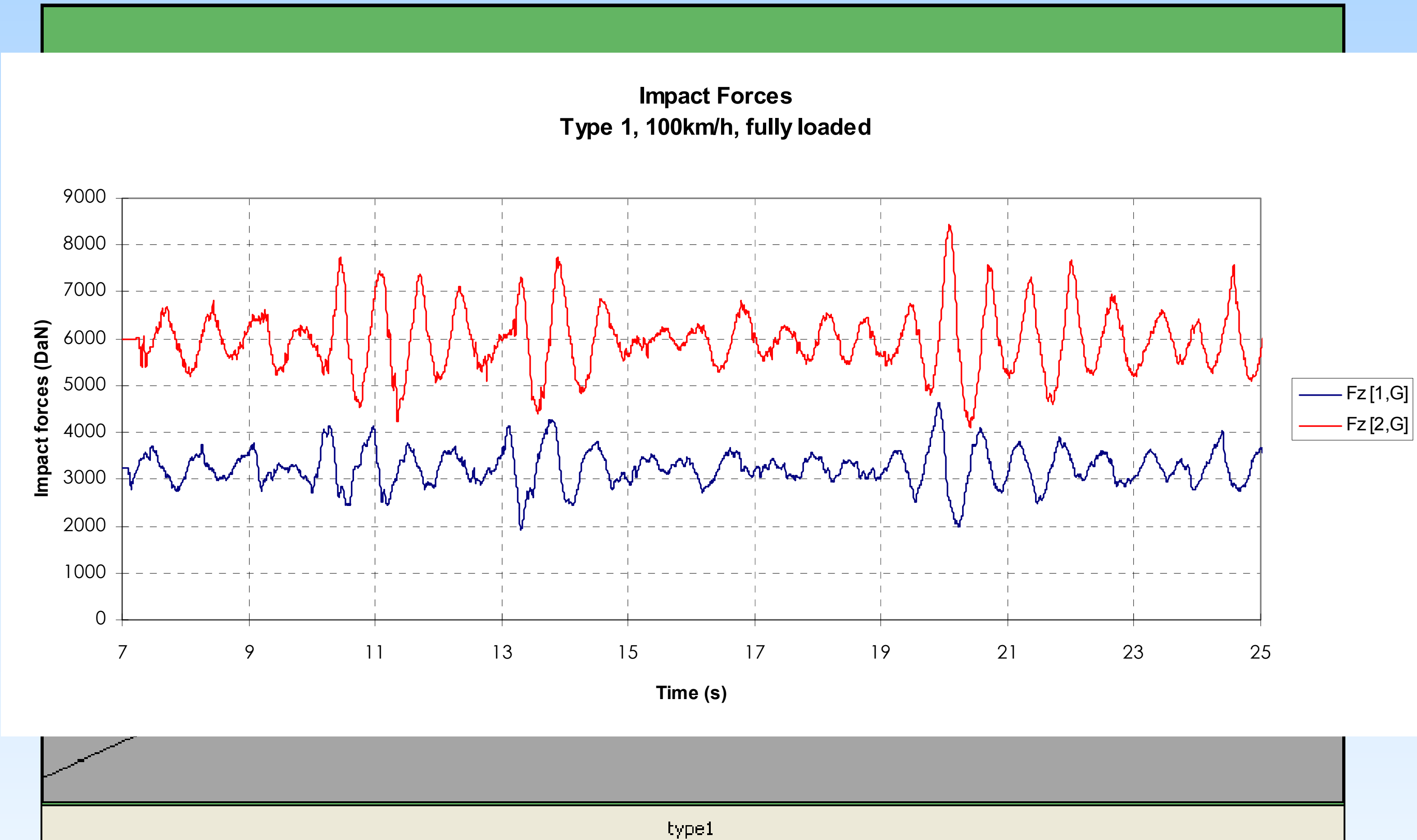
Introduction and objectives

- Objectives : Weighing truck axles in road traffic for legal applications (road pricing and enforcement)
- Multiple-Sensor WIM (MS-WIM) principle :
  - Axle impact forces variation along the road profile induces that one sensor's probability to measure the static weight is almost null
  - MS-WIM array (~ 5-15 piezoelectric bars) to repeat the measurement and sample the impact force
  - Static weight estimation algorithms (SAve, SR or ML1/2)

Static weight estimation algorithms

- Simple Averaging (SAve) : Mean of the measurements of each sensor of the array
- Signal Reconstruction (SR) : Deterministic approach consisting of a reconstruction of the continuous impact force which is averaged on a lenth L determined with an extended Kalman filtering procedure WAVE -LCPC
- Maximum of Likelihood (ML) : Probabilistic method based on a Maximum of Likelihood estimator and a signal modeling of the dynamic forces with 1 or 2 sine WAVE - CUED

Experiment - Simulation software



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etc…

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Experiment - Test site

- Real data : recorded on A31 motorway (near Metz)
- MS-WIM array : 16 piezoceramic strip sensors spaced by 1.6m linked to a Hestia data logger
- Great scattering of the results due to the special lateral location of the traffic

A31 test site

Experiment - Test plan

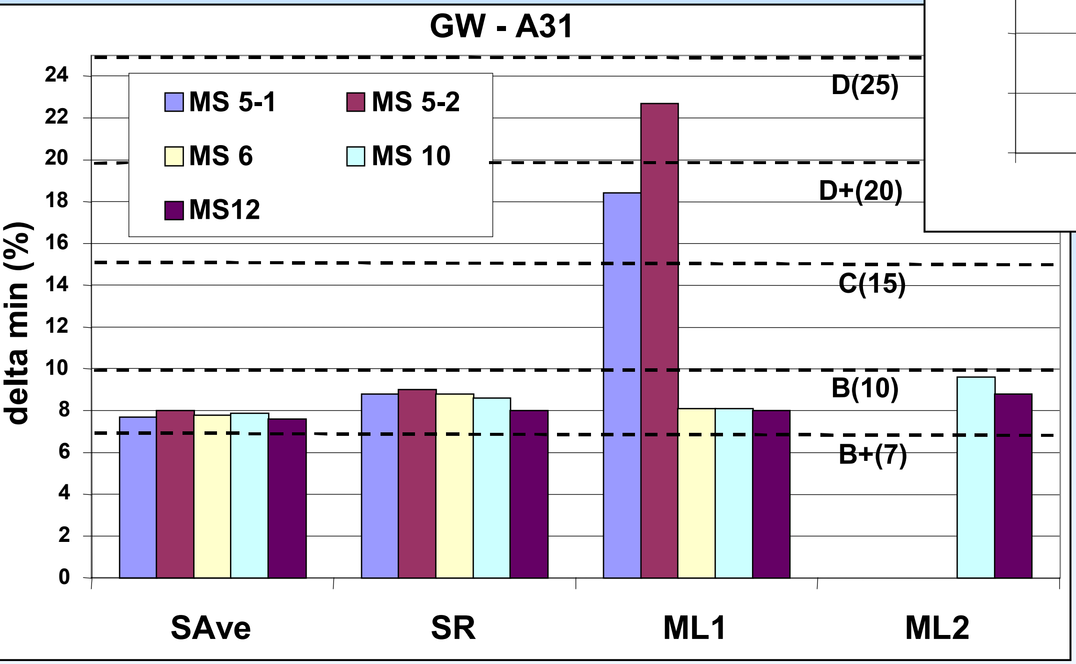
- Simulated data :
  - Type 1 truck (rigid with 2 axles)
  - 4 levels of load (empty, half loaded, fully loaded and 15% overloaded)
  - 3 speeds (60, 80, and 100 km/h)
  - RN10 (near Trappes) road profile
  - 3 arrays (with different sensor numbers and different spacing)
  - Sensor noise simulation $= +/- (WIM/20 \times rand + 0.5 \times rand)$ where rand is an uniformly distributed random variable in [0,1]
  - Data used for three estimation algorithms : SAve, SR, ML1 and ML2
- Real data :
  - 200 pre-weighed trucks from June 1998 to March 2000
  - 5 sub-arrays considered with 5, 5, 6, 10, and 12 bars

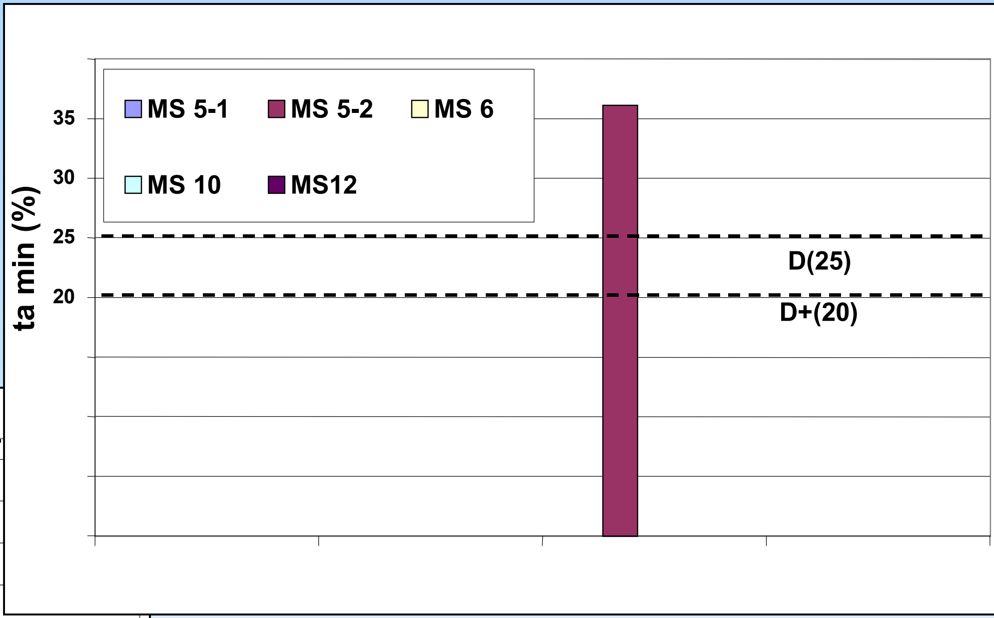
Results

- Computation time :
  - SAve and ML1 give very low computational times for one axle (less than 0.01seconds)
  - SR and ML2 need respectively 18 and 15 seconds per one axle
- Outliers :
  - Outliers were detected with a Dixon test (level of confidence 95%)
  - With simulated data, only ML2 provided outliers : 33% (8 outliers) due to a failure of convergence
  - With real data sample (1034 axles) :
    - Save : 2.6% of outliers
    - SR : 1.9% of outliers
    - ML1 : 14.5% of outliers
    - ML2 : 7.8% of outliers

Results - Real data

- Performance of each method
  - A(5) and B+(7) never reached whatever the method except for AoG and GoA criterium (B+(7))
  - ML very sensitive to the nb of bars

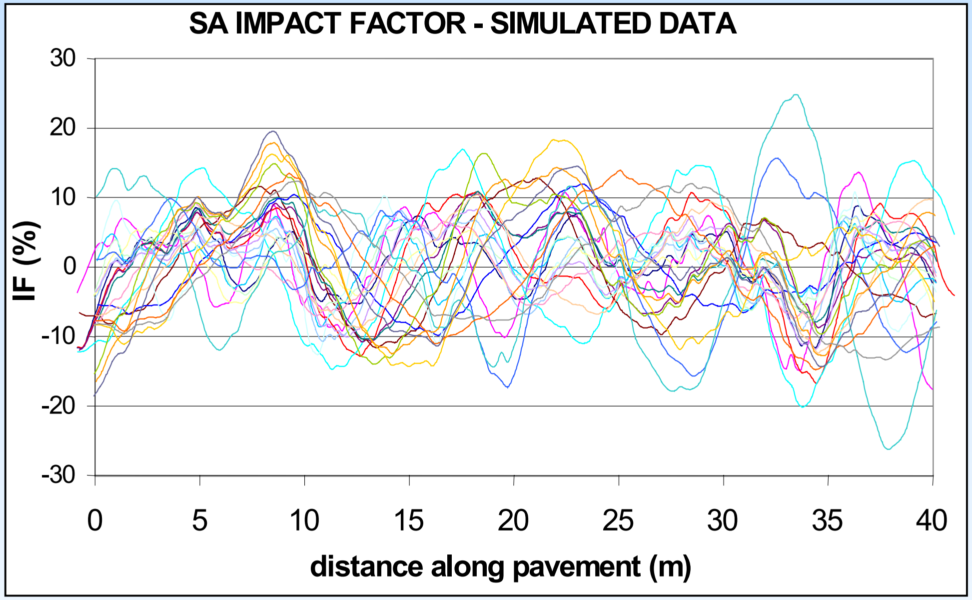


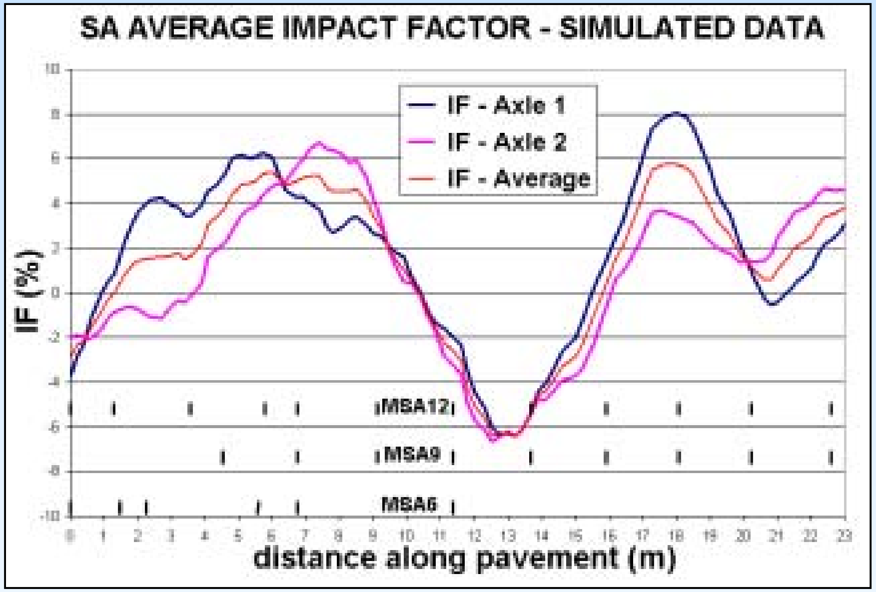


- Save and SR show very close results
  - Arrays design not optimal for Save which induces bias (spatial repeatability)
  - Data are affected by trucks special lateral location

Results - Simulated data

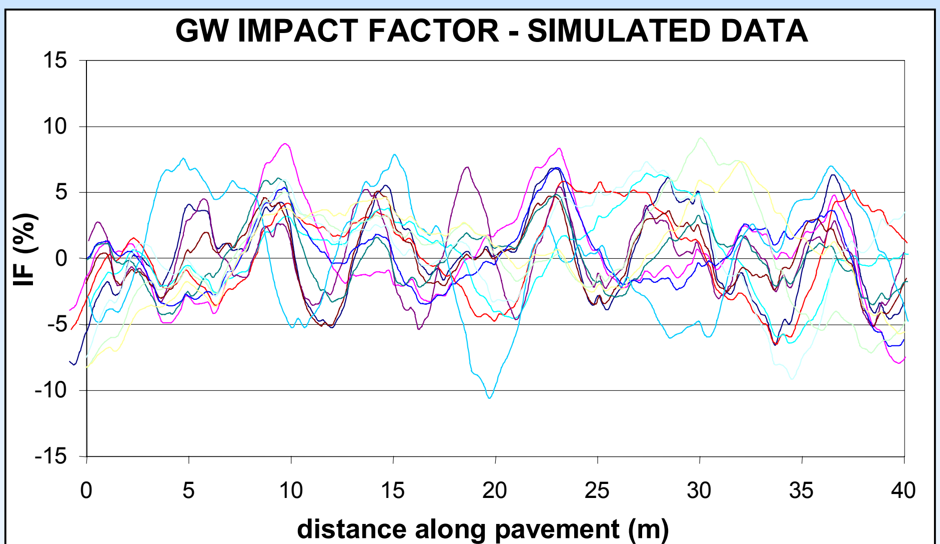
- Impact factor for SA
  - IF = relative error of impact force with respect to static load
  - Within 20% (good pavement)
  - Evidence of spatial repeatability

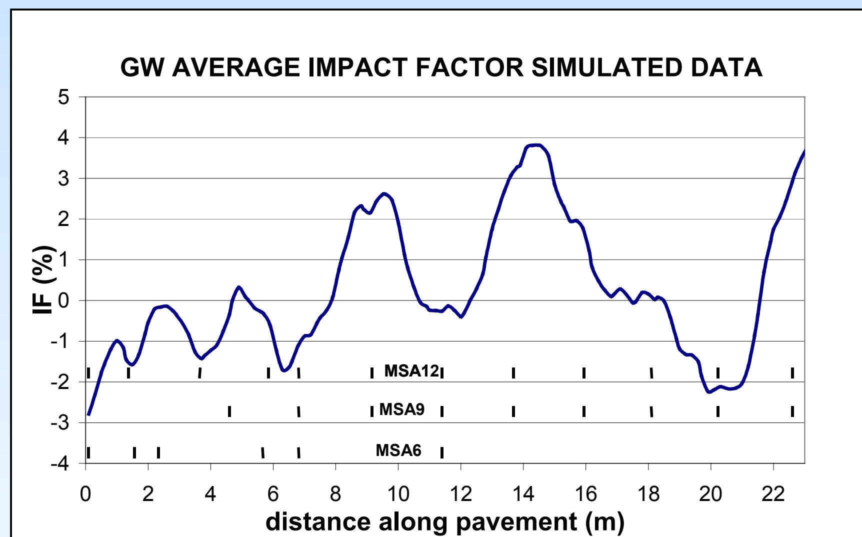




Results - Simulated data

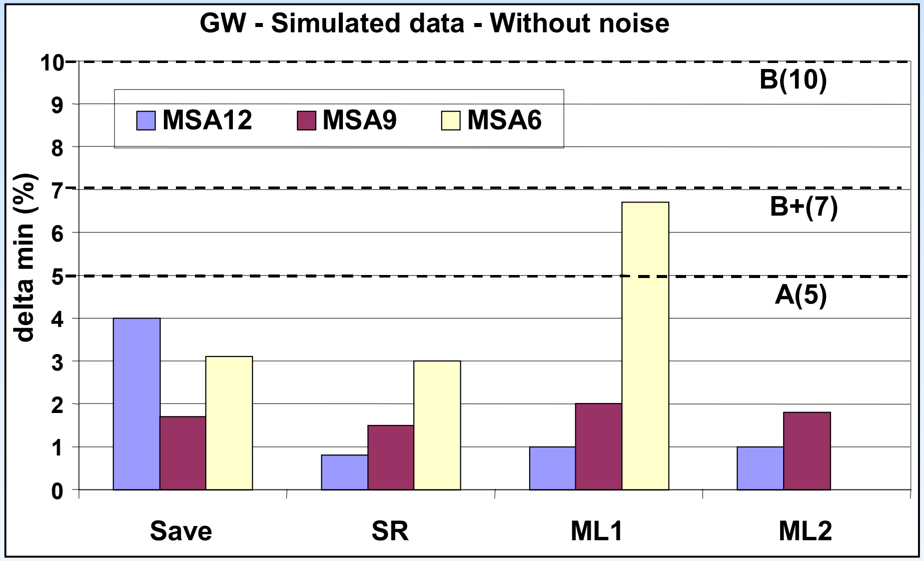
- <u>Impact factor for GW</u>
  - Within 5% (good pavement)
  - Spatial repeatability evidence affected by lack of signal stabilization : simulations begins 30meters before the first bar instead of 50 to 100m because of the bounce frequency
  - 5 first bars of MSA12 and all the bars of MSA6 underweight the GW
  - Most accurate array expected regarding to Impact Factor analysis : MSA9

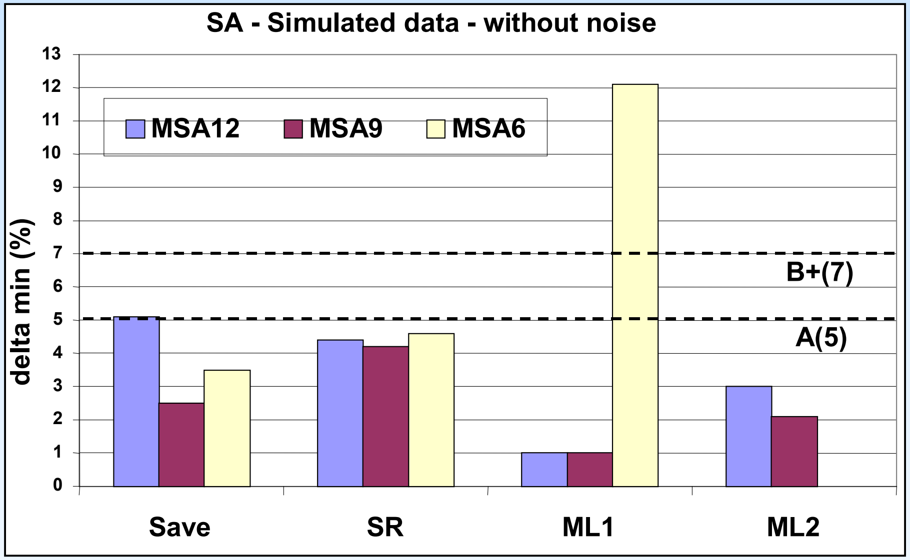




Results - Simulated data

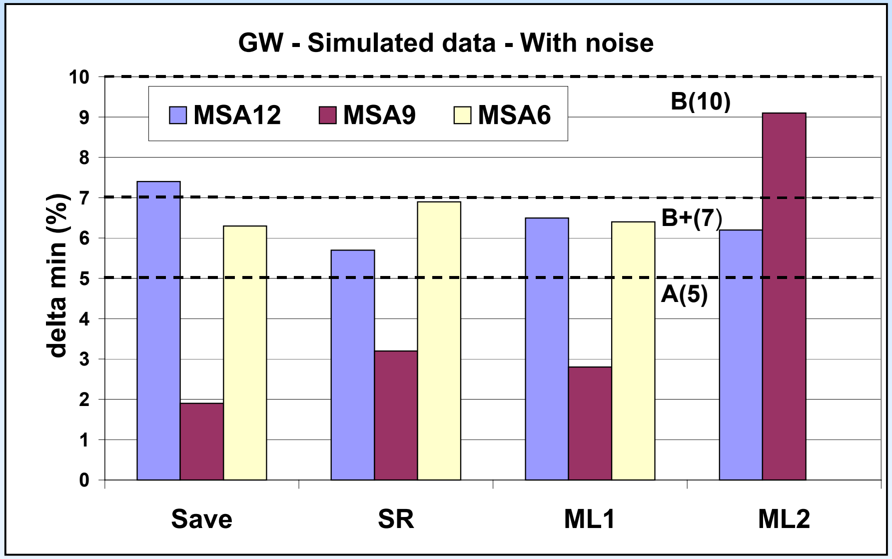
- Data without noise
  - A(5) whatever the method (except MSA6 and ML1)
  - With SAve method, MSA9 gives the best results as expected regarding to spatial repeatability and optimal sensor spacing
  - Other methods accuracy increase with the number of sensors, for GW estimation: they are less sensitive to the sensor spacing than Save
  - For SA criterion, SR, ML1, ML2 are independent on the number of sensors but require a minimum of sensors to be efficient (5 for SR and 9 for ML1 and 2)

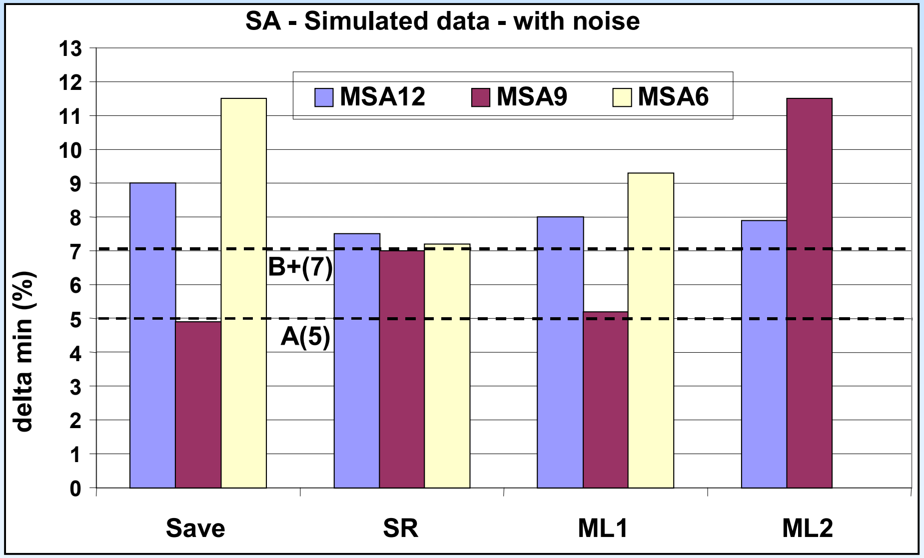




Results - Simulated data

- <u>Noisy data</u>
  - A(5) obtained with MSA9 whatever the method considered
  - Same conclusions as without noise can be done about the different methods, except MSA12 and SR for GW
  - All the benefits of the advanced algorithms is hidden by the sensor noise effect





Conclusions

- SAve method accuracy highly depends on the array design : not only the vehicle bounce motion eigenfrequency , but also the axle hop eigenfrequency should be considered in the optimization of the array
- ML methods require a minimum of 9 sensors to be efficient but both give rather good results for SA
- The advantage of SR method (robustness to sensor spacing and vehicles frequencies) may only be shown without noise (or with a low noise level)
- Without noise, accuracy class A(5) is reached whatever the method used. With noisy data, the accuracy drops down to class B+(7) or B(10), even with 9 or 12 sensors
- More accurate sensors and/or more robust (regarding to sensor noise) algorithms should allow to improve accuracy as it is necessary for enforcement applications